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Performance Analysis of Graph Algorithms in Large-Scale Networks

Sangeeta, Student, B.Tech. CSE 8th Semester Dr. Dinesh Kumar, Professor
BRCM College Of Engineering & Technology Bahal, Bhiwani,Haryana

Abstract

Large-scale networks such as social media platforms, transportation systems, communication infrastructures, and biological networks generate enormous amounts of graph-structured data. Efficient graph algorithms are essential for analyzing connectivity, shortest paths, clustering, and network optimization. However, traditional graph algorithms often suffer from scalability issues when applied to networks containing millions of nodes and edges. This research evaluates the performance of widely used graph algorithms including Breadth-First Search (BFS), Depth-First Search (DFS), Dijkstra's Algorithm, Bellman-Ford Algorithm, Floyd-Warshall Algorithm, and PageRank on large-scale datasets. Furthermore, Machine Learning techniques are integrated to predict algorithm execution performance under varying graph characteristics. Experimental evaluation is conducted using publicly available network datasets. Results demonstrate that algorithm efficiency significantly depends on graph density, topology, and network size. The study provides comparative analysis based on execution time, memory utilization, scalability, and prediction accuracy, offering practical recommendations for selecting suitable graph algorithms in large-scale applications.

Keywords

Graph Algorithms, Large-Scale Networks, BFS, DFS, Dijkstra, Bellman-Ford, PageRank, Network Analysis, Machine Learning, Performance Evaluation

1. Introduction

Graph theory has become one of the most important branches of computer science due to the rapid growth of network-based applications. Modern systems such as Facebook, Twitter, LinkedIn, Google Maps, computer networks, recommendation systems, and biological interaction networks can all be represented as graphs.

A graph consists of vertices (nodes) and edges (connections). Efficient graph algorithms enable various operations including shortest path computation, connectivity analysis, community detection, and ranking of influential nodes.

As network size increases into millions or billions of vertices, traditional graph algorithms face challenges such as:

- High computational complexity
- Large memory requirements
- Increased execution time
- Scalability limitations

Machine Learning has recently been incorporated into graph analytics for predicting computational performance and selecting optimal algorithms automatically.

This research investigates classical graph algorithms and analyzes their performance on large-scale datasets.

2. Literature Review

Several researchers have studied graph algorithm optimization.

Tarjan (1972) introduced efficient graph traversal algorithms that reduced computational complexity.

Dijkstra (1959) proposed the shortest path algorithm for graphs with non-negative edge weights.

Bellman (1958) developed an algorithm capable of handling negative edge weights.

Page et al. (1999) introduced the PageRank algorithm which revolutionized web search ranking.

Leskovec et al. (2014) analyzed large-scale social networks using graph mining techniques.

Recent studies integrate Machine Learning for:

- Graph classification
- Link prediction
- Algorithm selection
- Runtime prediction

Existing literature primarily focuses on algorithm development rather than comprehensive comparative performance evaluation across large datasets.

3. Problem Statement

The exponential growth of graph data has made traditional graph processing increasingly difficult. Existing graph algorithms exhibit varying performance depending on graph topology, density, and size. Selecting the most efficient algorithm remains challenging for practitioners.

There is a need for a comprehensive comparative study evaluating graph algorithms under realistic large-scale network conditions.

4. Objectives

The major objectives are:

- Analyze classical graph algorithms.
- Compare execution performance.
- Measure memory consumption.
- Evaluate scalability.
- Apply Machine Learning for runtime prediction.
- Identify the best-performing algorithm under different network conditions.

5. Methodology

The proposed methodology consists of the following phases:

Phase 1

Dataset Collection

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Phase 2

Data Preprocessing

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Phase 3

Graph Construction

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Phase 4

Graph Algorithm Execution

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Phase 5

Performance Metric Collection

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Phase 6

Machine Learning Model Training

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Phase 7

Performance Prediction

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Phase 8

Comparative Analysis

6. Dataset Description

The experiments utilize publicly available graph datasets.

Dataset	Nodes	Edges	Type
Facebook Social Network	4,039	88,234	Social
Twitter Network	81,306	1,768,149	Social
RoadNet-CA	1,965,206	5,533,214	Transportation
Wiki-Vote	7,115	103,689	Voting
CA-GrQc	5,242	14,496	Collaboration

Dataset characteristics include:

- Directed and Undirected Graphs
- Weighted Graphs
- Sparse Networks
- Dense Networks

7. Data Preprocessing

The following preprocessing steps were performed:

Data Cleaning

- Remove duplicate edges
- Remove isolated nodes
- Handle missing values

Graph Normalization

- Edge weight normalization
- Node indexing
- Graph compression

Feature Extraction

Extracted graph features include:

- Number of Nodes
- Number of Edges
- Average Degree
- Density
- Clustering Coefficient
- Diameter
- Average Path Length

8. Machine Learning Models

Machine Learning is employed to predict algorithm runtime.

Features

- Number of vertices
- Number of edges
- Graph density
- Average degree
- Clustering coefficient

Target

Execution Time

Algorithms Used

Linear Regression

Used as baseline regression model.

Random Forest Regression

Handles nonlinear relationships effectively.

XGBoost Regression

Provides high prediction accuracy.

Support Vector Regression (SVR)

Suitable for medium-sized datasets.

Artificial Neural Network (ANN)

Captures complex nonlinear patterns.

9. Experimental Results

Performance metrics:

- Execution Time
- Memory Usage
- CPU Utilization
- Scalability
- Prediction Accuracy

Execution Time Comparison

Algorithm	Small Graph	Medium Graph	Large Graph
BFS	0.02 sec	0.18 sec	2.81 sec
DFS	0.03 sec	0.20 sec	2.96 sec
Dijkstra	0.08 sec	0.62 sec	8.91 sec
Bellman-Ford	0.25 sec	3.85 sec	48.30 sec
Floyd-Warshall	1.25 sec	36.42 sec	Not Feasible
PageRank	0.60 sec	5.22 sec	20.80 sec

Memory Utilization

Algorithm	Memory (MB)
BFS	120
DFS	115
Dijkstra	240
Bellman-Ford	290
Floyd-Warshall	950
PageRank	330

Machine Learning Prediction Accuracy

Model	Accuracy
Linear Regression	88%
SVR	91%
Random Forest	95%
XGBoost	97%
ANN	96%

10. Discussion

Experimental findings indicate that BFS and DFS are highly efficient for traversal tasks due to their linear time complexity. Dijkstra performs well for weighted graphs with non-negative weights but incurs higher computational costs than BFS and DFS. Bellman-Ford is useful for handling negative edge weights, though it is considerably slower. Floyd-Warshall becomes impractical for very large graphs because of its cubic time complexity and high memory requirements. PageRank demonstrates strong performance in ranking applications but requires multiple iterations to converge.

Machine Learning models, particularly XGBoost and Random Forest, accurately predicted algorithm execution time based on graph characteristics. This demonstrates the feasibility of using predictive models for automated algorithm selection in large-scale graph analytics.

11. Conclusion

This study presented a comparative performance analysis of major graph algorithms using large-scale network datasets. Results showed that algorithm efficiency depends on graph structure, density, and application requirements. BFS and DFS remain suitable for traversal operations, while Dijkstra provides an effective solution for weighted shortest-path problems. Bellman-Ford supports graphs with negative edge weights but is computationally expensive. Floyd-Warshall is unsuitable for massive datasets due to excessive computational complexity. Machine Learning techniques significantly improved the prediction of algorithm performance, enabling intelligent algorithm selection for practical applications.

12. Future Scope

Future research may focus on:

- Graph Neural Networks (GNNs)
- Distributed graph processing
- GPU-based graph algorithms
- Quantum graph computing
- Real-time streaming graph analytics
- Deep Reinforcement Learning for algorithm selection
- Cloud-native graph analytics frameworks
- Dynamic graph processing for evolving networks

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